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# Option Hedging with Risk Averse Reinforcement Learning

Edoardo Vittori

Based on a work done with Michele Trapletti and Marcello Restelli

**Option Hedging** 

**Reinforcement Learning Intro** 

State of the Art

Risk Averse RL

**Experimental results** 

#### Conclusions

**Option hedging**: trading the *underlying asset* in order to minimize the price swings generated by the option (controlling risk).

#### <sup>3</sup> Reinforcement Learning Intro



- the action  $a_t \in [0, 1]$  the hedging portfolio
- the state  $s_t = (S_t, C_t, \frac{\partial C_t}{\partial S_t})$  $\frac{\partial C_t}{\partial S_t}, a_{t-1})$
- the reward  $R(s_t, a_t) = C_{t+1}(S_{t+1}) C_t(S_t) a_t \cdot (S_{t+1} S_t) c(n)$
- transaction costs  $c(n) = 0.05 \cdot (|n| + 0.01n^2)$ ,  $n = a_t a_{t-1}$

**Returns** 

$$
G(\tau) = \sum_{t=0}^{\infty} \gamma^t R_t
$$

**Action-Value function** 

$$
Q_{\pi}(s, a) = \mathop{\mathbb{E}}_{\tau \sim \pi} [G(\tau)|s_0 = s, a_0 = a]
$$

**Objective** 

$$
J = \max_{\pi} \mathop{\mathbb{E}}_{\tau \sim \pi} [G(\tau))]
$$

**Policy Search vs Value Based approaches** 

Reinforcement Learning in Finance

## RL in Hedging

- ' [\(Halperin, 2017\)](#page-16-0)
- [\(Halperin, 2019\)](#page-16-1)
- [\(Kolm and Ritter, 2019a\)](#page-16-2)
- [\(Kolm and Ritter, 2019b\)](#page-16-3)
- [\(Buehler et al., 2019\)](#page-16-4)
- [\(Cao et al., 2019\)](#page-16-5)

#### Risk Averse Reinforcement Learning

- Reward volatility
	- ' [\(Bisi et al., 2020\)](#page-16-6)
- Utility based
	- [\(Moldovan and Abbeel, 2012\)](#page-17-0)
	- [\(Shen et al., 2014\)](#page-17-1)
- Coherent Risk Measures
	- [\(Morimura et al., 2010\)](#page-17-2)
	- ' [\(Tamar et al., 2017\)](#page-17-3)
	- [\(Chow et al., 2017\)](#page-16-7)
- **Variance of the returns** 
	- ' [\(Sobel, 1982\)](#page-17-4)
	- ' [\(Tamar and Mannor, 2013\)](#page-17-5)
	- ' [\(Prashanth and Ghavamzadeh, 2014\)](#page-17-6)

#### Variance/Volatility relation <sup>6</sup>



$$
\sigma_{\pi}^2 \leqslant \frac{\nu_{\pi}^2}{(1-\gamma)^2}
$$

#### Reward volatility

$$
\nu_{\pi}^{2} = (1 - \gamma) \mathop{\mathbb{E}}_{\substack{s_0 \sim \mu \\ a_t \sim \pi(\cdot | s_t) \\ s_{t+1} \sim \mathcal{P}(\cdot | s_t, a_t)}} \left[ \sum_{t=0}^{\infty} \gamma^t \left( \mathcal{R}(s_t, a_t) - J_{\pi} \right)^2 \right]
$$

**Mean-volatility objective** 

$$
\eta_{\pi} := J_{\pi} - \lambda \nu_{\pi}^2
$$

**Trust Region Volatility Optimization-TRVO** [\(Bisi et al., 2020\)](#page-16-6)

#### Vanilla call option

- $\bullet$  time to maturity  $= 60$  days
- unitary notional
- $\bullet$  implied volatility = 20%
- $\bullet$  interest rates  $= 0$
- $K (= S_0) = 100$
- starting price (ATM) option  $\sim 3.24$
- starting delta  $= 0.5$

#### Simulated Market

- ' geometric brownian motion  $dS_t = \mu S_t dt + \sigma S_t dW_t$
- $\bullet$  no drift
- $\sigma = 20\%$
- $S_0 = 100$
- 5 time steps per day



 $\Rightarrow$  delta hedge with no costs  $\rightarrow$  average p&l  $\sim$  0, volatility  $\sim$  0.16

### $Adding costs$  10

We considered h.c.  $\sim 0.05|a|$ ,  $\sim$  the Euro Stoxx 50 or FTSE MIB future.

- More liquid listed products (S&P 500) have lower minimal costs
- Less liquid listed or OTC (vanilla, flow) instruments have significantly higher costs



- The agent now has something to optimize: costs vs. volatility
- Costs give a role to the risk aversion factor



 $\Rightarrow$  delta hedge with no costs  $\rightarrow$  average p&l  $\sim$  -0.3, volatility  $\sim$  0.18



#### Experimental Results: Pareto Plot **13** and 13



#### **Contributions**

**Proved experimentally that the hedging strategy learnt by the model dominates** the delta hedge

Future works

- Extend to more complex derivatives
- $\blacksquare$  Extend to a portfolio of options
- **Decide not only how much but also when to hedge**

**Contacts** 

- Edoardo Vittori edoardo.vittori@polimi.it
- Michele Trapletti michele.trapletti@intesasanpaolo.com
- **Marcello Restelli marcello.restelli@polimi.it**

# Thank You for Your Attention!

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